An Efficient Approach to Cattle Identification Using Muzzle Prints

Dr Anusha Edwin
Assistant Professor, Department of Mathematics, Mar Ivanios College (Autonomous).
Thiruvananthapuram, Kerala-695015, India

***Abstract*— Muzzle print analysis has emerged as a promising biometric approach for identifying individual cattle. This study proposes an identification framework based on Speeded-Up Robust Features (SURF), an image-processing technique used to extract distinctive features from muzzle print images. SURF employs a Hessian-matrix-based detector to locate significant keypoints and a descriptor to represent the local characteristics surrounding them. By using integral images to accelerate computations, the method reduces processing time while maintaining effective feature extraction. Its ability to handle variations in image scale and orientation makes SURF suitable for detecting and matching muzzle patterns under different imaging conditions.**

The proposed system utilizes Speeded-Up Robust Features (SURF) to identify and extract distinctive patterns from cattle muzzle print images. The extracted features are matched and classified using the Euclidean distance metric to determine the similarity between images. To assess the effectiveness of this method, its recognition performance is compared with that of a Principal Component Analysis (PCA)-based approach employing a fuzzy distance measure. This comparative evaluation focuses on the identification accuracy and robustness of both techniques, highlighting their suitability for cattle muzzle print recognition under varying image conditions.

***Index Terms*— Cattle muzzle print identification, Speeded-Up Robust Features (SURF), Principal Component Analysis (PCA), keypoint detection, feature extraction and description, feature matching, Euclidean distance metric, fuzzy distance-based classification, Gaussian function, and recognition performance evaluation.**

I. INTRODUCTION

The word biometrics is derived from the Greek term's bios, meaning "life," and metron, meaning "measurement." It refers to the identification or verification of individuals or animals based on their unique physiological or behavioral traits [1]. In contrast to conventional identification techniques that rely on keys, passwords, or other external credentials, biometric methods use characteristics inherent to the subject, reducing the likelihood of identification failures caused by loss, forgetfulness, or unauthorized transfer. These advantages make biometrics a promising approach to improving the reliability of animal identification. An animal biometric identifier can be described as a measurable and distinctive physical, anatomical, or biological feature that remains sufficiently consistent over time to distinguish one animal from another [2].

The muzzle, commonly known as the snout or nose, exhibits a distinctive skin texture characterized by an irregular distribution of ridges and grooves. The arrangement of these surface features differs among individual animals, providing a potential basis for biometric identification. Similar to human fingerprints, cattle muzzle patterns can serve as individual identifying characteristics because of their distinctiveness and relative stability over time. These properties make muzzle-based recognition a promising approach for reliable and long-term cattle identification. Figure 1 illustrates muzzle print images obtained from two different cattle.

This study investigates cattle identification through the analysis of muzzle-print patterns. Distinctive features are extracted from muzzle images using two image-processing techniques: Principal Component Analysis (PCA) and Speeded-Up Robust Features (SURF) [3]. The resulting feature representations are then used to identify individual cattle through classification based on Euclidean distance and a fuzzy distance measure [4]. A comparative evaluation is conducted to assess the recognition performance of

these methods and determine their suitability for accurate and reliable cattle muzzle-print identification.

II. CATTLE MUZZLE PRINT RECOGNITION USING SURF-BASED FEATURE EXTRACTION

SURF (Speeded-Up Robust Features) [3] is used to establish point correspondences between muzzle-print images. The recognition process can be broadly organized into three major stages:

1. Interest Point Detection
2. Feature Description
3. Feature Matching

Distinctive image structures, including corners, intersections, and blob-like regions, can be identified as keypoints for feature analysis. These points represent salient locations that help characterize an image and facilitate reliable feature matching. A key requirement of an effective interest-point detection method is repeatability, which refers to its ability to identify corresponding keypoints consistently across images of the same object despite variations in scale, rotation, and viewing conditions. This property is essential for achieving robust and accurate image recognition.

Once the keypoints have been identified, a feature descriptor is computed to capture the distinctive information in the local region around each point. An effective descriptor should preserve relevant image characteristics while minimizing the influence of noise, small positional shifts, lighting variations, and geometric changes. This enables corresponding regions across different cattle muzzle images to be represented consistently, supporting reliable feature comparison and matching during the recognition process.

The final stage involves matching the feature descriptors obtained from different muzzle images. SURF provides a compact feature representation, with the commonly used SURF descriptor consisting of 64 elements (1 × 64). This representation provides a balance between feature distinctiveness and computational efficiency, thereby facilitating faster comparison and matching of muzzle-print images.

This section describes the key stages involved in SURF-based recognition, with particular emphasis on the Haar wavelet-based feature descriptor, training procedure, and testing process.

2.1 Haar Wavelet-Based Descriptor

Construct square window of size 20S, where S is scale, centered on the interest point and oriented along the orientation vector. For preserving spatial information, the region is divided into 4X4 smaller square subregions. Haar wavelet responses in horizontal dx and vertical direction dy are calculated [3]. For each sub region, a 1×4 feature vector is formed with

$$v = (\sum dx, \sum dy, \sum |dx|, \sum |dy|)$$

Calculating v for all 4×4 regions, a descriptor of length 64 is formed. Wavelet responses are invariant to illumination. Scale invariance is achieved by mapping descriptor into a unit vector.

2.2 Training Phase

1. Collect and normalize all training muzzle print images.
2. Extract SURF feature of each muzzle image.
3. Represent each image by a feature vector.
4. Store all feature vectors in Database.

2.3 Testing Phase

1) Collect and normalize the test muzzle print image.
2) Extract the features of the collected image using SURF.
3) Find Euclidean distance between testing image feature vector with database feature vectors.

III. CATTLE MUZZLE PRINT RECOGNITION USING PCA AND FUZZY DISTANCE-BASED CLASSIFICATION

In this section important steps in PCA based recognition [5] viz. PCA with Euclidean, Fuzzy distance measure [4], Fuzzification and accuracy measurement, PCA with Fuzzy distance-based training and testing are discussed.

3.1 Muzzle Print Recognition Using PCA

Muzzle print recognition using PCA and Euclidean classifier is summarized below.

1. Collect a set of 'M' muzzle images and perform following. ($M = 40,\ \tau_1, \tau_2, \tau_3, \dots, \tau_M$). The average muzzle of the set is defined by

$$\psi = \frac{1}{M}\sum_{n=1}^{M} \tau_n (1)$$

Calculate the difference image between each input image and average muzzle image.

$\Phi_i = \Gamma_i - \psi$ (2)

These Φ_i are then used for principal component analysis, in which the data is best described by using eigen vector u_k and eigen values λ_k.

Build the matrix A of size $N^2 \times M$.

$A = [\Phi_1, \Phi_2, \Phi_3, \dots, \Phi_M]$(3)

2. Calculate the matrix L using eqn 4.

$L = A^T A$ (4)

and find M eigen vectors v_i of L with highest corresponding eigen values.

3.Calculate eigen muzzle U using equation 5

$U = AV$ (5)

4. Calculate weight vector Ω_i for each muzzle images (eqn 6). Calculate the threshold θ (eqn 7) that defines maximum allowable distance from any muzzle class.

$\Omega_i = u^T \Phi_i$(6)

$\theta = 0.46 \max \|\Omega_i - \Omega_j\|$(7)

for $i = 1,2, \dots, M; j = 1,2, \dots M.$

5. For a new muzzle image repeat 2 to 4 and classify according to eqn 8.

$$\left\{ \begin{array}{c} \text{If } \theta \le \zeta, \text{not a muzzle image;} \\ \text{If } \theta > \zeta, \theta > \varepsilon_{min}, \\ \text{it is a known muzzle corresponding } \varepsilon_{min}; \\ \text{Otherwise, a new muzzle image.} \end{array} \right\} \quad (8)$$

IV. FUZZY DISTANCE-BASED CLASSIFICATION

Fuzzy distance measure [4] is used for the identification of different objects such as images. Fuzzy distance measure is mainly based on operations on fuzzy sets. The resemblance between two objects is defined by a similarity or dissimilarity measure. The resemblance value increases when similarity value increases or distance measure (dissimilarity) value decreases. Thus, distance measure and similarity measure are dual concepts.

$\text{distance measure} = 1 - \text{similarity measure}$

Most commonly used fuzzy distance measure is Euclidean distance measure [4]

$$d_2(A, B) = \frac{1}{\sqrt{n}} \sqrt{\sum_{i=1}^{n} \left(\mu_A^i(x) - \mu_B^i(x)\right)^2} \quad (9)$$

Fuzzification and Accuracy Measurement

For fuzzification of feature vector, extracted using PCA, Gaussian function [7] is used. Membership function is given by

$$\mu(f) = e^{-0.5\left(\frac{f-m}{\sigma}\right)^2} \quad (10)$$

where σ is the standard deviation from mean and m is the mean of fuzzy set. As per texture in image, mean value will change. The performance of the system can be measured by using accuracy [6]. Accuracy gives correctness of identification procedure. The accuracy of identification system is given by

$$\text{Accuracy}(\%) = \left(100 - \frac{(\text{FAR}(\%) + \text{FRR}(\%))}{2}\right) \quad (11)$$

Where FRR is False Rejection Rate and FAR is False Acceptance Rate. FAR is the rate at which non-authorised muzzle is authorized as genuine. FRR is the rate at which genuine muzzle getting rejected. If FRR and FAR decreases, accuracy increases.

4.1 Training Phase

Step 1. Collect and normalize the muzzle print image.

Step 2. Extract the features of the training image using PCA extraction method.

Step 3. Represent each image by one feature vector.

Step 4. Store the Database and find the distance measures among them.

4.2 Testing Phase

Step 1. Collect and normalize the muzzle print image.

Step 2. Extract the features of the testing image using PCA.

Step 3. Compare feature vectors of testing image and training images using fuzzy distance measure.

Step 4. Matching to find muzzle or not and position as minimum distance value, if muzzle.

Training and Testing Phases are given in Figure 2.

V. MATERIALS AND METHODOLOGY

The muzzle photos have been taken from Jersey kinds of beef cattle race. Special permission has been taken from Kerala Government for collecting muzzle photos from Kudappanakkunnu Farm, Trivandrum, Kerala, India. The set of muzzle photos are standardized in orientation and scale manually. A rectangular region with minimum distance between nostrils with 300X300 size is taken as Region of Interest (ROI, Fig.3).

The experiments are done using a PC with intel core I5-4200M running at 2.5Ghz, and 4GB RAM. The PC

is installed with MATLAB in windows R 64 bit. Programs in MATLAB are written for PCA and Fuzzy distance

VI. ANALYSIS OF RESULTS AND PERFORMANCE EVALUATION

In our work the minimum image portion between muzzle nostrils is taken and normalized to 300X300 pixels. For each image, feature vectors are calculated using PCA. Initially using Euclidean distance measurement classification is done and accuracy values (eqn.11) are noted. Then these PCA features are fuzzified using Gaussian function (eqn. 10). Cattle classification is done using fuzzy distance measure (eqn.9). Accuracy values are again noted and compared. Same is repeated for SURF based recognition. Muzzle images of 40 cows are collected and stored in database. Algorithm is tested for 5, 15, 25 and 35 with other images as unknown. The results are shown below.

The average accuracy of PCA with Euclidean is 58%, PCA with fuzzy similarity is 85% and with SURF is 100%. Here we can see that SURF method gives better results as that of PCA. SURF method works well with image deformations like scaling, rotation etc but more sensitive to noise.

VII. CONCLUSION

This study proposes a cattle identification method based on Speeded-Up Robust Features (SURF) to recognize distinctive muzzle patterns under variations in image scale and orientation. In the proposed framework, salient features are extracted from muzzle images and encoded into SURF descriptors. The extracted feature representations are then compared with those of stored reference images using the Euclidean distance metric to determine the similarity between the test image and the available samples, thereby facilitating the identification of individual cattle.

The effectiveness of the proposed SURF-based recognition method is assessed through a comparative study with Principal Component Analysis (PCA), employing both Euclidean distance and fuzzy distance measures for classification. The experimental findings demonstrate that the SURF-based method achieves better recognition performance than the PCA-based approaches considered in this study.

Despite its promising recognition performance, the SURF-based method may be sensitive to noise and image-quality variations that affect the reliability of extracted features. Future research could therefore focus on enhancing the noise tolerance of the recognition framework to improve its accuracy, stability, and robustness under diverse imaging conditions.

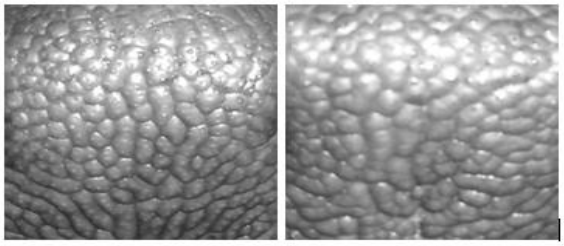

Figure 1. Two muzzle images

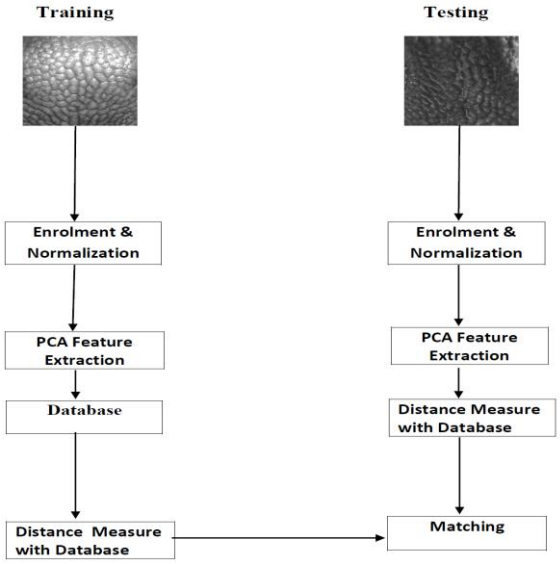

Figure 2: PCA with Fuzzy distance-based Cattle Identification System

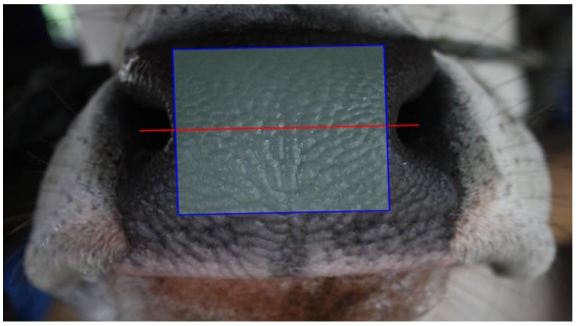

Figure 3. Region of Interest (ROI) of the muzzle photo

Table 1. Muzzle print recognition results

Number of Images	05	15	25	35
Accuracy (SURF with Euclidean)	100	100	100	100
Accuracy (PCA with Fuzzy distance)	94	90	87	70
Accuracy (PCA with Euclidean)	74	58	50	50

REFERENCES

[1] Bovik, Ed., *Handbook of Image and Video Processing*, 2nd ed. Academic Press, 2005, pp. 749–869.

[2] U. G. Barron, F. Butler, K. McDonnell, and S. Ward, "The end of the identity crisis? Advances in biometric markers for animal identification," *Irish Veterinary Journal*, vol. 62, pp. 204–208, 2009.

[3] H. Bay, A. Ess, T. Tuytelaars, and L. Van Gool, "Speeded-up robust features (SURF)," *Computer Vision and Image Understanding*, vol. 110, pp. 346–359, 2008.

[4] G. Lu and R. Liu, "Discrimination for fuzzy sets related to NTV metric," *IAENG International Journal of Applied Mathematics*, vol. 43, pp. 204–208, 2013.

[5] Barry, U. A. Gonzales Barron, K. McDonnell, F. Butler, and S. Ward, "Using muzzle pattern recognition as a biometric approach for cattle identification," *American Society of Agricultural and Biological Engineers*, vol. 50, pp. 1073–1080, 2007.

[6] J. Malik and D. Girdhar, "Reference threshold calculation for biometric authentication," *International Journal of Image, Graphics and Signal Processing*, vol. 2, pp. 46–53, 2014.

[7] S. M. Mukane, S. R. Gengaje, and D. S. Bormane, "Scale invariant texture classification using fuzzy logic," *International Journal of Scientific & Engineering Research*, vol. 3, pp. 1–4, 2012.

[8] M. Sonka, V. Hlavac, and R. Boyle, *Image Processing, Analysis, and Machine Vision*. Cengage Learning, 2013, pp. 72–73.

[9] T. J. Ross, *Fuzzy Logic with Engineering Applications*, 3rd ed. Wiley India Pvt. Ltd., 2013.